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Collaborative Signal and Information Processing for Target Detection with Heterogeneous Sensor Networks

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Abstract

In this paper, an approach for target detection and acquisition with heterogeneous sensor networks through strategic resource allocation and coordination is presented. Based on sensor management and collaborative signal and information processing, low-capacity low-cost sensors are strategically deployed to guide and cue scarce high-performance sensors in the network to improve the data quality, with which the mission is eventually completed more efficiently with lower cost. We focus on the problem of designing such a network system in which issues of resource selection and allocation, system behavior and capacity, target behavior and patterns, the environment, and multiple constraints such as the cost must be addressed simultaneously. Simulation results offer significant insight into sensor selection and network operation, and demonstrate the great benefits introduced by guided search in an application of hunting down and capturing hostile vehicles on the battlefield.

Keywords: Sensor management; Collaborative signal and information processing; Heterogeneous sensor networks; Array signal processing

Introduction

With the advancements in technologies, it is becoming increasingly feasible to conceive and deploy large-scale sensor networks for a wide variety of applications such as elderly assistance, traffic control, homeland security, military surveillance, and environmental monitoring [1]. Significant work has gone into the development of algorithms to perform a variety of tasks including detection, localization, classification, identification and tracking of one or more targets in the sensor field, and numerous approaches based on Collaborative Signal and Information Processing (CSIP) have been proposed in the literature, see, for example [2,3]. In the scenarios involving multiple targets, data association of measurements from multiple sensors is known to be NP-hard. Multiple hypothesis tracking (MHT) [4] and Markov chain Monte Carlo data association (MCMCDA) [5] are possible solutions to this tough problem at the cost of long latency and extensive computation.

Processing the signal from distributed but networked sensors collaboratively can be treated as an extension of multi-channel array signal processing, where the multiple sensors are collocated with a typical spacing of half a wavelength of the impinging waves and the centralized algorithms based on the relative phases and amplitudes of the wave across the sensors are utilized to obtain the optimal solutions. Array signal processing is essential in most sensor array based systems and has made significant success in a wide variety of applications including modern radar [6-12], underwater sonar [13-15], wireless communications [16-21], intelligent transportation systems [22-24], non-destructive evaluation [25-27], and ultrasound imaging [28]. However, the applications of these algorithms to wireless sensor networks are not straightforward, mainly due to the constraints intrinsic to most of the sensor nodes on energy, communications, computation and size, and the distributed, simple and efficient alternatives that can deliver sub-optimal solutions while meeting the practical constraints have received considerable attention.

We address the problem of target detection and acquisition with a heterogeneous sensor network in this paper. We take as a sample task

the problem of hunting down and capturing hostile vehicles on the battlefield, with a sensor network consisting of Unattended Ground Sensors (UGS) and Unmanned Aerial Vehicles (UAV). A UGS may be one sensor node equipped with collocated multi-modality sensors or a small cluster of distributed sensors, but assume to be simple in function, cheap, static but rapidly deployable. The location of each UGS is assumed to be known in advance obtained from on-board GPS receivers or a self-localization algorithm. A UAV is very expensive, mobile and with high performance, equipped with cameras and the necessary image recognition software, and would be able to identify and localize the potential targets with high accuracy. The goal of the whole network system is to distinguish the hostile vehicles from the civilian vehicles, and then to locate and track the hostile vehicles, and eventually capture or destroy the hostile vehicles. There are many real-world applications with parallel environment and requirements such as search and rescue options, surveillance, tracking of moving parts, and search and capture missions. In some cases, the potential targets are intelligent and actively avoiding being captured as in the application addressed in this paper, whereas in other cases their motion is approximately random as in rescue options.

The problem is to study how to guide the UAVs effectively with a network of UGS nodes, and then capture the targets efficiently and accurately. A key element of this problem is the assumption that resources are limited, for example, constrained by the budget, and the choices are driven by trade-offs between the performance and the cost. The capability of the above-mentioned network to perform its tasks depends on several factors, including the amount of available UGS/

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UAV sensors, the sensory range and accuracy, the sensor deployment strategy and lifetime, environment characteristics, target behaviors, and etc. The question that we are investigating is that: with a finite budget, what is the best way to combine and allocate resources so as to maximize the performance level of the sensor network in terms of, for example, the target destruction rate and time?

In this paper, we propose an efficient algorithm to tackle this problem and show that it is effective in reducing the capturing time via simulations. With the data provided by the UGS network, the target vehicles' moving patterns are identified and they are further classified into wheeled and tracked categories of vehicles. The locations of the potential hostile vehicles are determined, predicted and tracked using different vehicle moving models, and the most efficient strategy for the deployment of the UAV fleet or other UGS clusters is decided, and eventually the UAV will confirm the targets and capture them. The rationale of our approach is that the low-cost low-capability sensors are strategically employed to cue and guide the high-performance but scare sensors to perform the task, through sensor management and strategic resource allocation and coordination placing the right sensors at the right locations on the right time.

The paper is organized as follows. Section 2 describes and formulates the problem at hand, and models this high dimensional design problem with a collection of autonomous decision-making entities, or agents. Section 3 discusses in details the collaborative signal and information processing algorithms for strategic resource allocation and coordination. Simulation results are given in Section 4 to evaluate the algorithms and demonstrate the benefits. The paper is then concluded.

Problem Formulation and Modelling

Problem description and formulation

To illustrate target detection and identification in complex environments with the aid of strategic resource allocation and coordination in heterogeneous sensor networks, we consider a specific problem where a sensor network consisting of UGS and UAVs is deployed on the battlefield, for the purpose of acquiring and eventually capturing the hostile vehicle targets. The vehicles are assumed to consist of three categories: hostile tracked vehicles, hostile wheeled vehicles, and civilian wheeled vehicles. In this scenario, the objective is to design rules for coordination and information sharing between UGS and UAVs to reduce the time required for clearing all the hostile vehicles with the constraint of total cost.

The system under consideration consists of three major components: a complex environment, vehicles, and sensors. The environment is a simplified two-dimensional urban grid of a pre-set, configurable size. The map is generated using a stochastic algorithm that ensures the resulting map is randomly created, but still follows a consistent pattern that resembles the layout of a city to a degree. Some buildings and forests are added into the map to complicate the terrain, which have impact on the sensors' accuracy such as the probability of detection and the probability of false alarm. Potential targets are road-bounded including hostile vehicles (either tracked or wheeled) and civilian vehicles (wheeled only). The vehicles traverse the environment by selecting starting points and destinations at random. They plan their routes by following the shortest path to their destinations, and are assumed to be confined in the environment if they are alive. The sensors consist of UGS and UAVs, which are imperfect, having a probability of reporting that a target is present when it isn't, as well as reporting that it

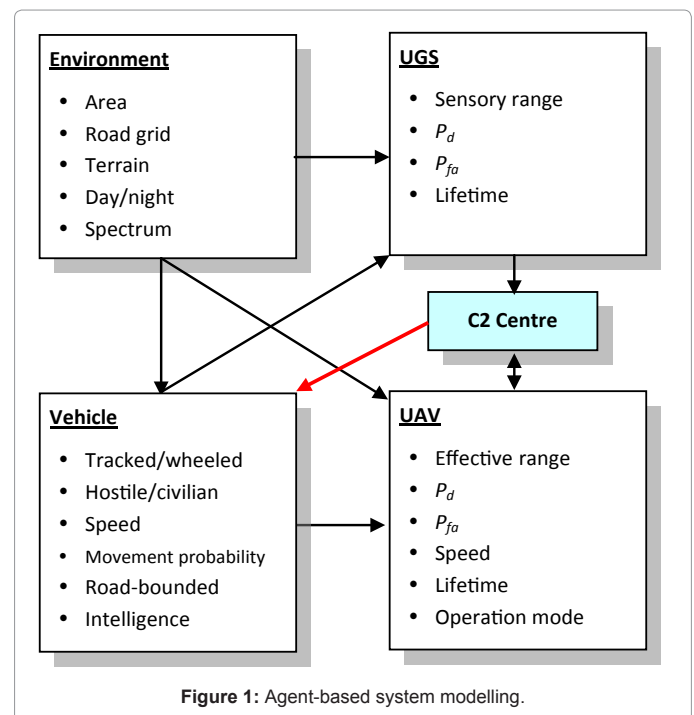
is not present when it is. It is assumed that the local data fusion within a UGS node is available, and no fusion within neighboring nodes is provided locally, but All UGS can transmit the detections back to the base station in the command and control (C2) centre. UGS has the ability to detect a vehicle in the vicinity, and classify it into tracked or wheeled vehicles using for example the spectrum based method [3], and cannot accurately localize or track the target. Each UAV is equipped with cameras, the necessary image recognition facility, and the laser range finder, and would be able to identify and localize the targets if they are within the range and field of view (FOV) of the camera. Each UAV maintains a direct communication link to the base station.

Agent-Based Modelling (ABM)

We use a modeling approach known as agent-based modeling [29] to study and simulate the high dimensional design space problem at hand. In this approach, systems are represented as collections of autonomous decision-making entities, called agents. Each agent individually assesses its situation and makes decisions based upon a set of behavioral rules. At the simplest level, an agent-based model consists of a system of agents and the relationships between them. Even a simple agent-based model can exhibit complex behavioral patterns and provide valuable insight about the dynamics of the real-world applications that it emulates.

The benefits of ABM over other modelling techniques can be captured in three statements [30]: 1) ABM captures emergent phenomena; 2) ABM provides a natural description of the complex systems; 3) ABM is flexible. The ability of ABM to deal with emergent phenomena is the main driving force behind its success as a complex adaptive system modelling tool. The fact that it provides a natural framework to describe complex systems combined with its flexibility makes ABM the tool of choice for the problem at hand.

The parameters modelling the environment, sensors and vehicles, and the relationship and interaction between them are shown in Figure 1. The environment has impact on the vehicle behaviors, detection



probability P_d and false alarm probability P_{fa} of UGS and UAVs due to the terrain and day/night variation. The C2 centre collects the rough target information from UGS, makes optimal task allocation and path scheduling for UAVs, and deploys munitions to destroy targets that are confirmed and localized by UAVs. Both UGS and UAVs have limited lifetime due to battery and petrol consumption, respectively.

Solution Approach

The algorithm for strategic resource allocation and coordination is shown below. Our approach specifies relatively simple local behavior to be adopted by each UGS and UAV, and the desirable global behavior arises from the interactions between them. N UGS are initially deployed at the junctions of roads to enhance the coverage efficiency because all the vehicles are assumed to be road bounded. If the vehicle behavior is known a priori, for example, the hostile vehicles are most likely coming from certain directions along certain roads, UGS can be placed strategically in those areas; otherwise, they are deployed randomly. At the beginning, M UAVs make autonomous search, where the term “autonomous” is compared to guided search cued by UGS. The UAVs may work in two ways: dividing the whole area into M zones and dispatching one UAV to each zone, or cooperatively searching for targets based on swarm intelligence [31]. Each UAV maintains a direct connection to the base station at the control centre, and all the UGS are networked and the detection information is sent to the base station either directly via the communication links or through multiple hops. The control centre maintains a two-dimensional map of the environment and the roads.

As illustrated in Figure 2, each UGS obtains its own sensor measurements, and makes a decision via the on-board data fusion. The results are contained in three categories: if no vehicles are detected in the vicinity, the result is 0; if tracked vehicles are detected, the result is 1; if only wheeled vehicles are detected, the result is 2. Assume UGS’

function to be simple: it cannot count, accurately locate, or track the targets. This assumption helps to alleviate UGS’ cost requirement. The results from the UGS are reported back to the control centre for data fusion which forms a preliminary search of the field. A probability method is then applied to the initial decisions to predict the vehicle locations to overcome the uncertainty caused by the delayed message, movement of the vehicles, and the inaccurate local information. A major challenge is how to associate the UGS detections with the correct targets, a method based on the principle of machine learning [32] is utilized in this work. After predicting the vehicle locations, the control centre designs the capture strategies. There are three options: 1) plan the most efficient pursuit trajectories of the UAV fleet based on the swarm intelligence; 2) rapidly deploy another set of UGS (with artillery or by operators) in the direction of the vehicle movement to track the vehicles; and 3) combined actions of decisions 1) and 2).

Assume n_t UGS report tracked detection 1, n_w UGS report wheeled detection 2, and the other $N-n_t-n_w$ UGS report null detection 0. If $n_t+n_w \geq M$ all M UAVs are involved in the task allocation and coordination; otherwise only n_t+n_w UAVs are involved and the remaining UAVs make autonomous search. Strategic deployment of multiple UAVs means task allocation and path planning for some destinations that must be visited and some risk sites that must be avoided. The flying time is a criterion used to measure the effectiveness of a schedule. A good schedule can guide the UAVs to all destination UGS as quickly as possible, before the targets move far away. When only one UAV is considered, the problem is similar to traveling salesman problem (TSP). In the scenarios involving multiple UAVs, the problem resembles Job-Shop Scheduling Problem (JSSP) [33]. Both TSP and JSSP are NP-hard and intensively studied in literature. In our system, the Particle Swarm Optimization (PSO) algorithm [34] is used to allocate tasks and design paths for each UAV. PSO is a recent addition to evolutionary algorithms first introduced by Eberhart and Kennedy in 1995. The foundation of PSO is based on the hypothesis that social sharing of information among conspecifics offers an evolutionary advantage. Partially inspired by animal social behaviors such as flocking of birds, PSO originally intends to graphically mimic the graceful way in which they find their food sources and save themselves from predators. It should be noted that if $n_t+n_w \gg M$, it is not necessary to devise a complete schedule to visit all n_t+n_w UGS, since after a long time, the targets have moved far away. The number of destination UGS considered in our algorithm is determined by the amount of UAVs, the sensory ranges of UGS and UAVs, the speed of the target vehicles and UAVs, target behavior, and etc. Another rule that should be pointed out is that, the task of searching for tracked vehicles has higher priority than that for wheeled vehicles, which has higher priority than autonomous search. Based on this rule, UAVs can be interrupted from current task and reallocated to perform higher priority tasks.

The algorithm will not terminate automatically. Even if all hostile vehicles have been destroyed (but this information has not been confirmed and notified to the control centre), civilian vehicles continue triggering UGS’ detections and UAVs’ guided search.

Simulation Results

The design space for the problem of resource allocation and behavioral coordination is complicated and high-dimensional, involving the amount of sensors, detection range and accuracy of sensors, coordination rules between sensors, in addition to the environment characteristics and target behaviors. In this section, we demonstrate 1) the effectiveness of agent-based modelling to this

The algorithm

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Initial placement of  $N$  UGS
Autonomous search by  $M$  UAVs
repeat
  for each UGS do
    Get own sensor measurements
    Data fusion for target detection and classification
    Send the decisions to C2 centre
  end for
  C2 centre: task allocation and path scheduling for UAVs
              performing lower-priority tasks
  for each UAV do
    Receive commands from C2 center
    Search the vicinity of destination UGS or make
      autonomous search
    if any targets are confirmed
      Localize the target
      Track the target while C2 center prepares
        munitions to destroy it
      Perform battle damage assessment (BDA)
    end if
  end for
until termination of operation
    
```

Figure 2: Algorithm for UGS and UAV coordination.

type of problem, 2) sensor selection and coordination strategies at the constraint of limited budget, and 3) benefits introduced by strategic sensor management and coordination. For the sake of simplicity, only two key dimensions, the amount and capability of sensors are explored, but we stress that other dimensions can be similarly treated.

We consider an urban area of 40km by 40km including 2500 uniformly distributed junctions. The target vehicles consist of 40 hostile tracked vehicles, 40 hostile wheeled vehicles and 400 civilian wheeled vehicles. All the vehicles are road bounded with a movement probability of 50%, and at a speed between 40km/h and 80km/h. UAV has two operation modes: cruising mode at a speed of 200km/h, and searching mode at a speed of 100km/h. The results are calculated based on an average over 30 runs.

In the first experiment, the amount of required UGS and UAVs is studied. Assume UGS' sensory range $r=0.5\text{km}$, the probability of detection $P_d=0.8$, and the probability of false alarm $P_{fa}=0.15$; UAV's sensory range $r=3\text{km}$, $P_d=0.8$, $P_{fa}=0.05$. Figure 3 shows the effectiveness, in terms of the half target destruction time, versus the number of UAVs, with certain amount of UGS. It is evident that, in all cases we have a consistent reduction in the target destruction time with the increase of UAVs, which corresponds to a higher cost. It is interesting to note that when the number of UAVs is greater than 5, too many UGS (for example, when the number of UGS increases from 40 to 100) may cause drawbacks, since P_{fa} is virtually increased due to large civilian vehicle detections which then triggers more vain UAV search. Another interesting point is the nonlinear change nature of the curves, which is common in the complex systems. For example, we can tell that when the UGS number is 40, increasing UAVs from 3 to 4 has a much greater impact than, say increasing UAVs from 9 to 10. The ability to find "tipping points" is a key driver of success in the analysis of complex systems of this type.

In the second experiment, the impact of UGS' detection range r , P_d and P_{fa} on the system effectiveness is studied. Figure 4 shows the half target destruction time versus r with certain P_d value and $P_{fa}=0.15$. Although the curves are not strictly monotonic due to the average over small number of trials, the trends and impact of these parameters on the target destruction time are clearly demonstrated. In general,

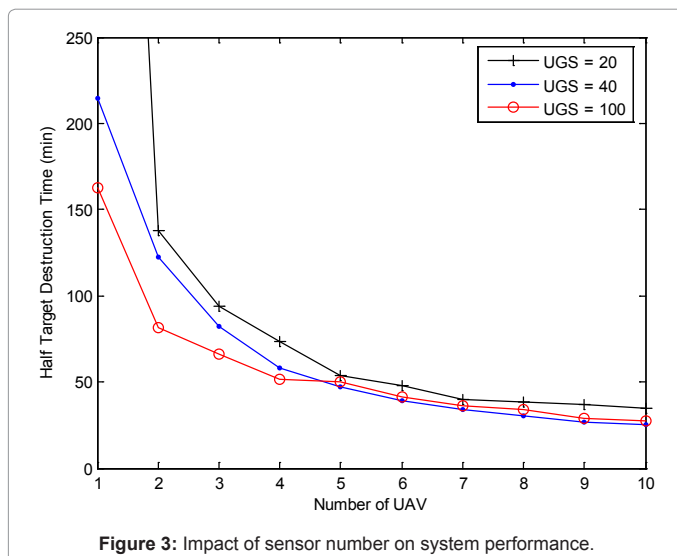


Figure 3: Impact of sensor number on system performance.

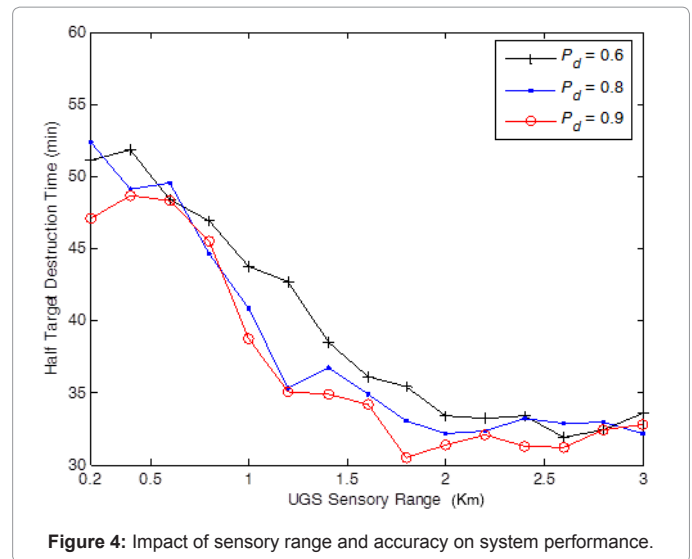


Figure 4: Impact of sensory range and accuracy on system performance.

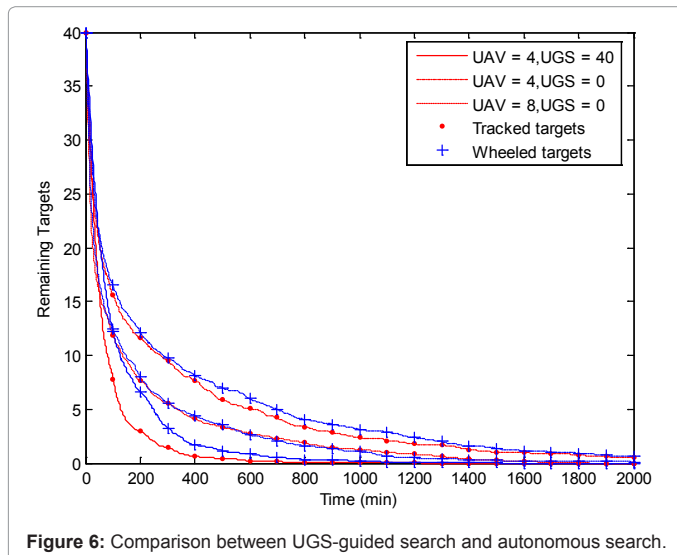
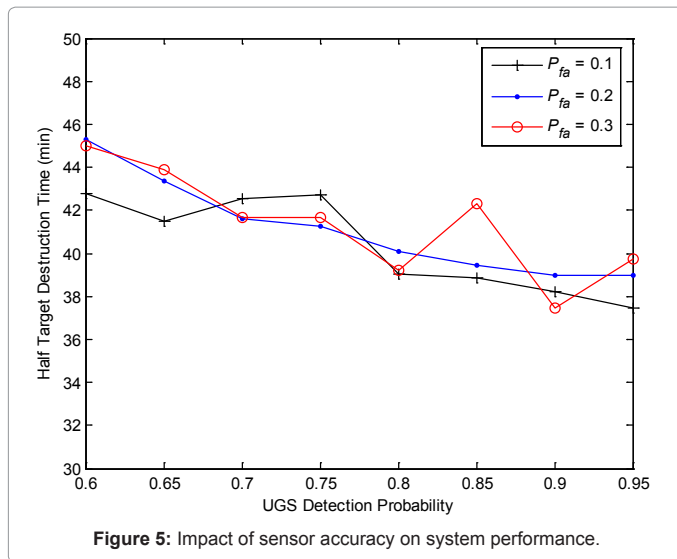
larger detection range and higher P_d of UGS, which corresponds to a higher cost, lead to faster target destruction. Figure 5 shows the target destruction time versus P_d with certain P_{fa} and $r=1\text{km}$. It is interesting to note that when P_d is high (for example, above 0.8), the system is more sensitive to P_{fa} by showing large fluctuations in the curves with P_d changing; however, when P_d is moderate (for example, between 0.6 and 0.8), the performance is more dominated by P_d , and lower P_{fa} causes more fluctuations as P_d varies. This phenomenon is of great practical interests to the system designers. Again, tipping points are identified in the system.

In the third experiment, the proposed method of UGS-guided search is compared with UAV's autonomous search. The UGS settings are $r=1$, $P_d=0.8$, $P_{fa}=0.2$. As shown in Figure 6, the solution involving 4 UAVs and 40 UGS is much more effective in terms of the half target destruction time, especially when the number of remaining targets is moderate or small. UAV is expensive high-end equipment, so the solution of 4 UAVs and a set of UGS is much cheaper than that involving 8 UAVs. For guided search, tracked vehicles are diminished faster than wheeled vehicles, since higher priority attention is given to tracked detections in our system based on our rules, and due to the assumption that all civilian vehicles are wheeled vehicles. For autonomous search, two types of vehicles are destroyed with a similar rate.

Conclusions and Future Work

In this paper, an approach for target detection and acquisition with a heterogeneous sensor network through sensor management and strategic resource allocation and coordination is presented. We focus on the problem of designing a network system in which resource constraints (such as the limited budget) and system behavior and performance must be addressed simultaneously. Although our work is only embryonic in nature, the results already offer significant insight into the resource selection and network operation, and demonstrate the great benefits in a sample battlefield application.

As future work, we will explore the applications of evolutionary algorithms as techniques to search the high dimensional problem space for an optimal solution, in terms of the amount of each type of sensors, the sensor range and accuracy, the inter-node data fusion algorithms,



network level resource allocation rules, with multiple constraints such as budget, communication range and link failure, and etc.

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